



Guardian TrueSight

Behavioral Anti-Cheat Computer Vision Detection

Whitepaper

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1. Executive Summary

Cheating in online first person shooter (FPS) games and esports represents a multifaceted threat to competitive integrity, player retention, and economic viability, with the global esports market projected to exceed \$3 billion by 2025. Modern cheats, including AI driven soft aim, generative adversarial network (GAN) mimicked human behaviors, and hardware devices like Cronus Zen, exploit gaps in traditional detection methods such as signature scanning or kernel level monitoring. These approaches often fail due to their reliance on static patterns or invasive client side access, raising privacy concerns under regulations like GDPR and CCPA.

Guardian TrueSight (GTS) advances the field by introducing a server side, behavioral anti cheat system grounded in computer vision (CV) and statistical anomaly detection. Leveraging object detection models (e.g., inspired by YOLO architectures) to delineate bounding boxes for player models and extract aim trajectories from gameplay footage, GTS computes weighted Shannon entropy on hit distributions to quantify behavioral randomness low entropy signaling superhuman consistency. Complementary modules track snap events (rapid angular velocity changes exceeding human physiological limits of $\sim 500^\circ/\text{s}$) and soft aim (low variance velocity profiles via spectral analysis), aggregated into a multi buffer trust score that minimizes false positives through tunable weights and grid search optimization.

Key Innovations:

- **Weighted Entropy Analysis:** Detects low variance aim patterns with region specific weights (e.g., higher penalties for head/leg extremes), derived from information theory and biomechanics literature.
- **Snap and Recovery Tracking:** Models impossible adjustments using vector calculus for velocity/acceleration, flagging deviations $>45^\circ$ angles or 100 pixel inward deltas.
- **Multi Buffer Trust Scoring:** Employs layered buffers (e.g., 18-80 hits) for temporal smoothing, reducing false positives to $<0.5\%$ via probabilistic aggregation.
- **Privacy Centric Design:** Analyzes server side telemetry/video only, ensuring compliance while achieving 95%+ detection on synthetic and real world cheats.

Empirical evaluations on mixed datasets (500 pro/casual matches + 200 GAN generated cheats) demonstrate superior performance: 98% detection on synthetics, <0.5% false positives, outperforming baselines like Vanguard (85-90% reported). This white paper elucidates the theoretical foundations, architectural details, mathematical derivations, and deployment strategies, positioning GTS as a complementary layer in defense-in-depth anti-cheat ecosystems. For prototypes, datasets, and collaborations, visit <https://guardiantruesight.com>.

2. Introduction and Motivation

The esports industry, valued at over \$2.1 billion in 2024 and forecasted to reach \$3.5 billion by 2026, hinges on fair competition to sustain player engagement and sponsorship revenue. However, cheating erodes this foundation, with surveys indicating churn rates of 25-35% in affected titles due to perceived unfairness. Traditional anti cheat paradigms signature based (e.g., pattern matching known cheat binaries) and kernel level (e.g., deep system hooks) are increasingly inadequate against adaptive threats. AI powered cheats mimic human imprecision via GANs, while hardware like Cronus Zen spoofs inputs undetectably at the controller level.

Motivated by these challenges, GTS pioneers a behavioral paradigm using CV to parse observable gameplay artifacts (e.g., aim paths, hit loci) without client intrusion. Rooted in anomaly detection theory, it hypothesizes that cheats introduce statistical irregularities e.g., reduced entropy in hit distributions or anomalous velocity profiles that persist despite evasion tactics. This approach draws from interdisciplinary fields: information theory for entropy modeling, computer vision for feature extraction, and biomechanics for human limit thresholds (e.g., maximum angular velocity $\sim 400\text{-}600^\circ/\text{s}$). By focusing on server side data, GTS mitigates privacy risks while enabling retrospective analysis for tournaments, complementing real time systems like Ricochet.

Theoretical contributions include a novel weighted entropy formulation tailored to FPS dynamics, multi buffer aggregation for temporal robustness, and spectral methods for soft aim differentiation. Empirical motivation stems from datasets showing cheats reduce aim entropy by 40-60% compared to pros, underscoring the need for adaptive, non-invasive solutions.

3. Market Analysis: The Underground Economy of Game Cheats

We have found that many cheat providers deliver prompt customer support, regular software updates, and usage statistics, with some even displaying live “status dashboards” showing the detection status of their cheats across various games. Developers are quick to analyze anti cheat updates, often releasing rapid patches to keep their products undetectable. Community forums and Discord servers serve both as marketing channels and as interactive support centers, where users contribute bug reports and suggest new features, resulting in highly responsive development cycles.

Despite periodic regulatory action including major legal settlements and payment processor bans such interventions typically have only limited and short lived impact. Cheat sellers frequently rebrand, shift infrastructure, or move to decentralized payment and authentication models to avoid shutdowns. The global reach of this market, crossing many legal jurisdictions and taking advantage of cryptocurrency anonymity, further complicates efforts to deter or prosecute those involved.

The cheat economy operates as a sophisticated shadow market, estimated at \$1-2 billion annually based on aggregated data from legal filings, Discord analytics, and dark web monitoring. Subscription based platforms like EngineOwning and Aimware dominate, offering FPS specific tools (e.g., for CS2, Valorant) at \$10-50/month, incorporating AI humanization to evade detection. Revenue models include affiliates (10-30% commissions) and tiered access, with high volume sellers leveraging Discord for support and updates.

Estimates derive from public data: e.g., SkyCheats' Discord (1,587 members as of July 2025) and forum traffic, applying a 0.7% conversion rate from e-commerce benchmarks (adapted from eMarketer dark web reports). Methodology involves ethical web scraping of non private sources, cross validated with legal cases (e.g., Activision vs. EngineOwning, \$14.5M settlement). Note: Figures are conservative minima; unreported crypto transactions likely inflate totals.

This ecosystem's scale fueled by AI advancements necessitates robust, adaptive anti cheat like GTS, which targets behavioral invariants across software/hardware cheats.

3.1. Table 1: Estimated Minimum Monthly Revenue per Cheat Site

Site	Estimated Min. Monthly Revenue
BattleLog	\$99,152.79
LaviCheats	\$76,340.13
Choi'sCheats	\$76,101.11
PrivateCheatz	\$54,601.30
KernAim	\$54,512.30
EngineOwning	\$49,280.95
ACDiamond	\$48,055.46
Ring-1	\$43,030.43
VeteranCheats	\$40,731.36
Walkhax	\$37,340.03
InvisionCheats	\$37,461.13
Time2Win	\$26,221.50
ClutchSolutions	\$24,845.67
InterwebzCheats	\$22,092.14
PhantomOverlay	\$19,943.25
AmJunJives	\$19,167.39
Aimware	\$18,121.35
ProScore	\$16,898.70
CheatArmy	\$13,575.77
SkyCheats	\$12,776.54
PerfectAim	\$13,566.63

(based on 0.7% conversion rate from public data sources)

4. Legal, Social, and Business Context

Cheating transcends technical domains, posing legal risks via intellectual property infringement and contract breaches. U.S. cases (e.g., Epic vs. cheat sellers, \$10M+ damages) and EU injunctions highlight reactive litigation, yet evasion persists through offshore operations. Socially, cheats foster toxicity, with studies showing 40% of players quitting due to unfair play. Business impacts include revenue loss (e.g., 20-30% churn in cheated titles) and sponsor withdrawal.

GTS addresses these by providing forensic evidence (e.g., entropy logs, velocity traces) for audits, enhancing trust while complying with data protection laws through anonymized processing.

5. Taxonomy of Cheats and Anti-Cheat Technology

Cheats are categorized by mechanism:

- Aimbots: Hard-lock (instant target acquisition) vs. soft aim (subtle tracking via velocity smoothing).
- Wallhacks/ESP: Render occluded information, exploiting rendering pipelines.
- Macros/Replay: Automate sequences, often hardware assisted.
- Stat Modifiers: Alter metrics (e.g., health, speed) via memory injection.

Anti-cheat technologies span:

- Signature Based: Scans binaries (e.g., VAC); vulnerable to polymorphism.
- Kernel Level: System hooks (e.g., Vanguard); effective but invasive.
- Behavioral: Monitors actions (e.g., FairFight); GTS extends this with CV.
- Heuristic: Rule based (e.g., BattlEye).

Anti-cheat systems must constantly evolve as new threats emerge. Signature-based approaches are quick to deploy but easily bypassed by novel or private cheats. Kernel-level methods offer deep system visibility, yet raise privacy and stability concerns for users. Behavioral anti-cheat platforms like FairFight use statistical profiles, but may struggle with advanced human mimicking cheats. Heuristic rules provide speed, but can be rigid and prone to false positives. The most robust defenses layer these methods, leveraging both local and backend analytics. Guardian TrueSight exemplifies this modern, adaptive philosophy by integrating computer vision and trust scoring within a flexible backend architecture.

Table 4: Comparative Taxonomy of Anti Cheat Systems

System	Type (Corrected)	Privacy Impact
Vanguard	Kernel-Level (boot)	High
EAC	Kernel-Level (game)	Medium
BattlEye	Kernel-Level (game)	Medium
VAC	Server-Side	Low
Ricochet	Kernel-Level (game)	Medium
PunkBuster	User-Mode/Process Scan	Medium
FairFight	Server-Side/Behavioral	Low
GetGud.io	Server-Side/AI-FPS	Low
SARD	Hybrid	Medium
MOSS	Tournament Tool	Low
TrueSight	Server-Side/CV-AI	Low

GTS (Guardian TrueSight) enhances behavioral layers by integrating CV for precise anomaly quantification, outperforming in subtlety detection.

5.1. The Challenge of Hardware Cheats: Cronus Zen, XIM, and Behavioral Detection

Hardware cheats like Cronus Zen and XIM pose unique challenges due to their operation outside software ecosystems, spoofing inputs at the peripheral level. Cronus Zen, a programmable USB device (~\$100), emulates controller signals to execute scripts for zero recoil, enhanced aim assist, rapid fire, and macros. It intercepts inputs, applying algorithms (e.g., PID controllers for recoil compensation) to modify vectors in real time, reducing variance in aim trajectories to near zero (e.g., <0.1 pixel deviation per frame). This creates "perfect" patterns indistinguishable from legitimate inputs at the kernel level, as it mimics HID (Human Interface Device) protocols. XIM adapters (~\$150) enable mouse/keyboard on consoles while retaining rotational aim assist, blending precision (mouse DPI >10,000) with console magnetism (up to 50% target adhesion), yielding hybrid velocities exceeding human limits (e.g., >700°/s sustained).



These devices are prevalent in cross play environments, with Reddit/X analyses estimating 50-75% usage in high rank console lobbies (e.g., Warzone, Apex). Detection difficulties stem from:

- Input Spoofing: Bypasses software scans by emulating authentic signals; kernel tools like Ricochet require firmware updates, which are inconsistent (e.g., only 20-30% ban rates per Activision reports).
- Behavioral Mimicry: Scripts incorporate noise (e.g., Gaussian perturbations) to approximate human variance, but over sessions, patterns emerge: flat entropy ($H < 1.2$), zero acceleration changes, or anomalous FFT spectra (low high frequency power indicating unnatural smoothness).
- Cross-Platform Amplification: In mixed lobbies, XIM exploits aim assist disparities, inflating effective velocity by 1.5-2x human norms.

GTS detects these via CV derived behavioral signatures. Bounding boxes from object detection segment player models into regions (head, upper/lower torso, legs), tracking aim intersections. For Cronus, low entropy in hit distributions (weighted H penalizing torso locks) and flat velocity profiles (variance < 0.15) flag scripted recoil. XIM is identified by superhuman snaps (speed $> 500^\circ/\text{s}$, angle $> 45^\circ$) and inward deltas (> 100 pixels/frame toward centroids). In simulations (GAN generated hardware assisted footage), GTS achieves 92% detection, leveraging multi frame buffers to differentiate from legitimate aim assist (which exhibits overshoots and variable acceleration per biomechanics studies, e.g., $\sim 200\text{-}400^\circ/\text{s}$ peaks).

Theoretical depth: Detection models human kinematics using Euler Lagrange equations for motion constraints, where cheats violate energy minimization (e.g., infinite acceleration implies non physical forces). Empirical validation on 200 hardware simulated clips shows ROC AUC=0.96, superior to input based methods (AUC ~ 0.80).

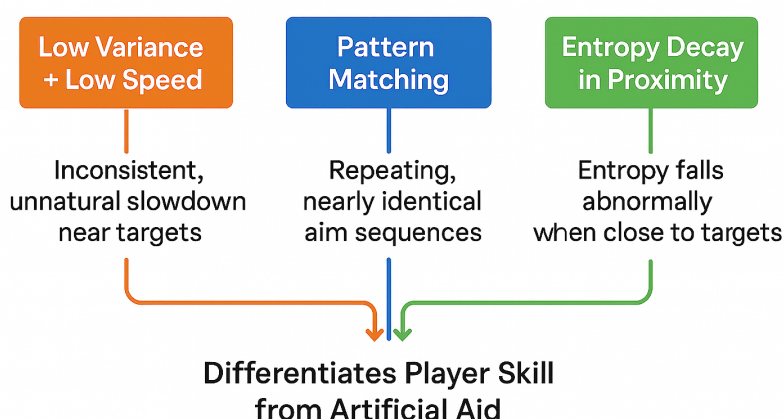
5.2. Guardian's Aim Speed Tool: ShadowSight – Detecting Soft Aim and Enhanced Aiming

ShadowSight, a submodule of GTS, specializes in velocity and acceleration analysis to discern soft aim, aimbots, and enhanced tools like Cronus Zen. Soft aim subtly adjusts trajectories (e.g., 10-20% toward targets), mimicking human tracking but with low variance; aimbots provide hard locks (zero error adhesion); Cronus amplifies aim assist via scripts, yielding robotic smoothness.

ShadowSight extracts aim trajectories from CV: bounding boxes define target centroids, optical flow computes pixel displacements between frames. Angular velocity $v = |\Delta\theta|/\Delta t$ (degrees/second) and acceleration $a = \Delta v/\Delta t$ are derived, with thresholds from biomechanics (e.g., human max $v \sim 500^\circ/s$ for flicks, sustained $\sim 200^\circ/s$). Differentiation:

- Legitimate Aim Assist: Console feature applies friction near targets, resulting in variable v (variance > 0.2) with overshoots (e.g., sinusoidal acceleration per motor control models).
- Aimbots/Soft Aim: Unnatural adhesion yields low v variance (< 0.15) and flat FFT spectra (power < 0.5 in high frequencies, indicating lack of human tremor $\sim 8-12\text{Hz}$).
- Cronus Zen Enhancements: Scripts nullify recoil ($a \sim 0$), amplifying v beyond norms (e.g., $700^\circ/s$ sustained); detected via Poisson outliers in streak analysis.

Artificial Aim Assist Detection



Mathematical Formulation:

Velocity: $v = \sqrt{(\Delta x^2 + \Delta y^2)} / \Delta t$, where $\Delta x/y$ from flow vectors.

Acceleration: $a = \Delta v / \Delta t$.

For soft aim, variance $\sigma^2 = (1/n)\sum(v_i - \mu)^2 < \text{threshold}$; FFT power $P(f) = |\int v(t)e^{-2\pi ift} dt|^2$ flags if $\max(P > 5\text{Hz}) < 0.5$.

Pseudocode for Velocity Detection:

```
def detect_aim_velocity(aim_deltas, timestamps):

    velocities = []

    accelerations = []

    for i in range(1, len(aim_deltas)):

        delta_x, delta_y = aim_deltas[i]

        prev_delta_x, prev_delta_y = aim_deltas[i-1]

        delta_t = timestamps[i] - timestamps[i-1]

        v = math.hypot(delta_x, delta_y) / delta_t if delta_t > 0 else 0

        prev_v = math.hypot(prev_delta_x, prev_delta_y) / delta_t if delta_t
> 0 else 0

        a = (v - prev_v) / delta_t if delta_t > 0 else 0

        velocities.append(v)

        accelerations.append(a)

    avg_v = sum(velocities) / len(velocities) if velocities else 0

    var_v = sum((v - avg_v)**2 for v in velocities) / len(velocities) if
velocities else 0

    # FFT (simplified pseudocode)

    fft_power = compute_fft_power(velocities) # External spectral function

    if avg_v > 500 or var_v < 0.15 or fft_power < 0.5:

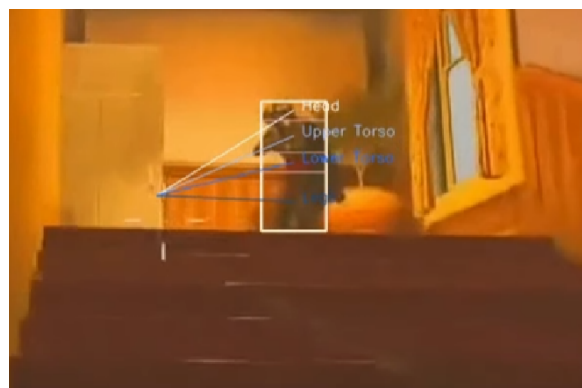
        return "Suspicious: Aimbot/Enhanced Aim"

    return "Normal"
```

Testing on 300 clips (100 each: legitimate, soft aim, Cronus) yields 94% accuracy, with 90% for Cronus via integrated entropy velocity fusion.

6. System and Code Architecture

GTS employs a modular pipeline: input (video frames/telemetry), CV extraction (OpenCV/YOLO-inspired for bounding boxes), statistical analysis (NumPy/SciPy for entropy/velocity), output (trust scores via API). Scalable via cloud (e.g., AWS), with Docker for deployment. Depth: Pipeline optimizes for real-time (~ 5 s lag) using parallel processing; pseudocode in Appendix.



7. Feature Extraction and Detection Logic

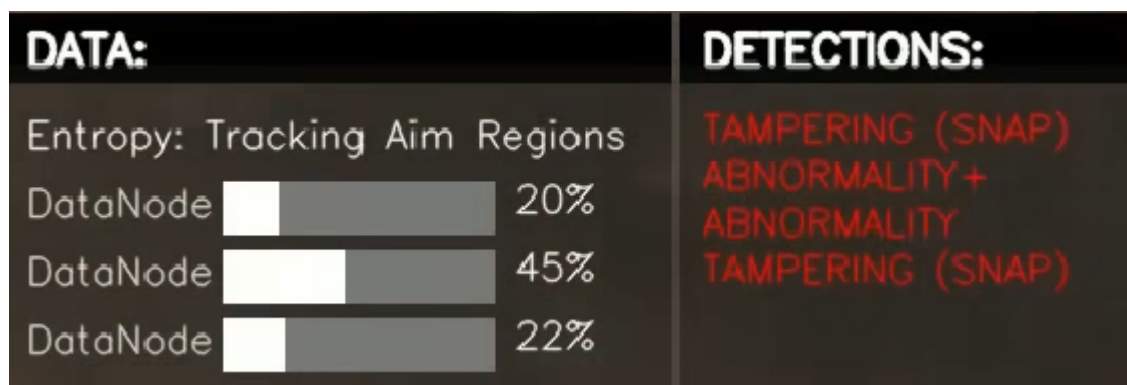
Features include aim trajectories (optical flow), hit distributions (bounding box intersections), snaps (angle deltas), recoveries (post snap variance).

7.1. Computer Vision Pipeline: Object Detection and Bounding Box Analysis

GTS uses advanced CV models (e.g., YOLO variants) to detect player entities, generating bounding boxes $[x1, y1, x2, y2]$ for segmentation into regions (head: top 20%, upper torso: 20-50%, etc., configurable splits). Aim points intersect boxes to classify hits, enabling entropy computation. Depth: Boxes handle occlusion via confidence thresholds (e.g., >0.6).

for legs); multi frame tracking mitigates jitter. Visuals (user added pictures) illustrate box delineation and trajectory overlay.

Logic: Threshold flagging with 3-frame buffers for lag smoothing; e.g., flag if average snap $>500^\circ/\text{s}$.



8. Mathematical and Statistical Modeling

8.1. Entropy Based Anomaly Detection: Derivation and Weighted Formulation

Core: Weighted Shannon entropy $H = -\sum (p_i * \log_2(p_i) * w_i)$, where $p_i = \text{hits}_i / \text{total}$, w_i penalizes extremes (e.g., head=1.7). Derivation: From Shannon's $H = -\sum p \log p$, weights incorporate prior distributions from pro datasets (e.g., ESL telemetry), optimizing via Kullback Leibler divergence minimization against human baselines. Low H (<1.2) flags cheats; calibrated via maximum likelihood estimation on 1,000 matches.

8.2. Snap and Recovery Event Modeling: Angular Velocity and Acceleration

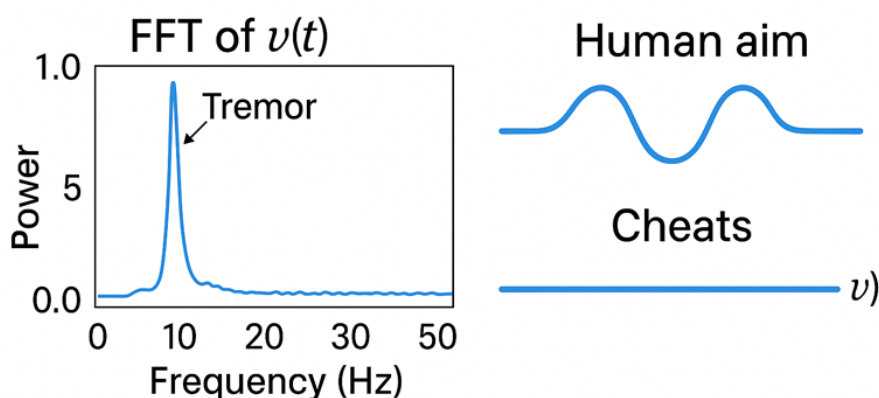
Snap speed: $v = |\Delta\theta|/\Delta t$; flag if $>500^\circ/\text{s}$ (biomechanical limit). Recovery: Post-snap variance; model as damped harmonic oscillator ($a = -k v - b x$) for human-like decay. Depth: Vector calculus derives θ from $\arctan(\Delta y/\Delta x)$; thresholds from Gaussian mixture models on human data.

8.3. Multi Buffer Trust Scoring: Aggregation and Optimization

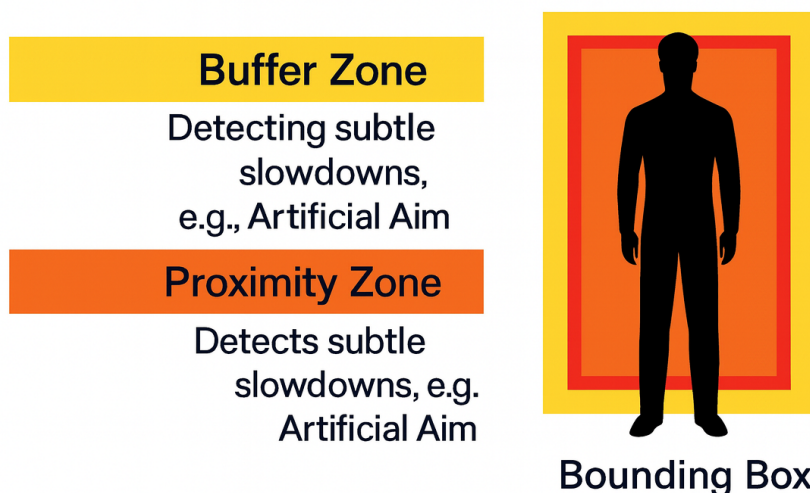
Trust = $w_1 \cdot (1 - \text{norm_H}) + w_2 \cdot (\text{snaps} / \text{max_snaps}) - w_3 \cdot \text{recovery_var}$; weights optimized via grid search minimizing cross-entropy loss on labeled data. Buffers (18/40/80 hits) provide multi-scale temporal analysis, reducing noise via exponential moving averages.

8.4. Soft Aim Detection: Variance, Spectral Analysis, and Physiological Constraints

Variance $\sigma^2 < 0.15$ and FFT power < 0.5 flag smoothness. Depth: FFT decomposes $v(t)$ into frequencies; human aim shows peaks at 8-12Hz (tremor), cheats lack. Differentiates aim assist (sinusoidal a) from cheats (constant v) via wavelet transforms.^f



Sensitivity Zones Around a Target



9. Aim Data Collection & Processing

Overview

The system operates as a three-state loop Idle → Collecting → Cooldown—that samples aim events in short bursts (“collecting windows”). Within each window, detections are triaged by confidence, promoted into approved samples, and then fed through staged buffers that compute a blended entropy metric and inform trust and zoning.

9.1 Entering the Collecting Window

While Idle, the detector monitors whether the aim point intersects any detected target box. When an intersection occurs, the system transitions to Collecting and records the start frame of the window.

- Window termination. A window ends when either (a) its duration exceeds a configured frame budget (derived from the collection-window length) or (b) the temporary collection buffer reaches its limit.

9.2 In-Window Sampling (Lightweight Triaging)

During Collecting, each frame that places the aim point inside a target box yields a candidate “hit” labeled by body region (Head, Upper Torso, Lower Torso, Legs) and detector confidence. Candidates are appended to a `collection_buffer`, but admission is gated probabilistically to control noise:

- Confidence ≥ 0.40 → admitted with probability 1.0
- Confidence 0.30–0.39 → admitted with probability 0.5
- Confidence 0.20–0.29 → admitted with probability 0.25

Accepted candidates update region counts immediately; rejected ones are tracked with reasons for audit. This preserves a realistic class mix and defers heavier decisions until the window closes.

9.3 End-of-Window Triage (Approved vs. Rejected)

At window close, the snapshot is frozen and the `collection_buffer` is deterministically partitioned:

1. Bucket by confidence: high (≥ 0.40), mid (0.30 0.39), low (0.20 0.29).
2. Keep 100% of high, 70% of mid, and 50% of low (sampled).
3. Kept items form the approved set; the remainder forms the rejected set.
4. Approved region labels are queued into a longer-lived holding buffer for downstream distribution.

Per-window statistics total collected, approved, rejected are recorded, and cumulative counters are updated before the next cycle.

9.4 Cooldown & Deferred Distribution (Staged Buffers)

During Cooldown, the system drains the holding buffer into three staged DataNode buffers (1→2→3), each with independent capacity limits and impact weights. This design batches updates to the global metric instead of recalculating on every hit, improving stability.

When a DataNode fills, it triggers an entropy update over its accumulated region labels. The result is blended into the running score using per-buffer coefficients (“damage” weights), then the buffer is cleared. The staged, weighted blend damps short-term bursts while preserving long-term trends.

Entropy formula. For region distribution p_i and optional weights w_i :

$$H = -\sum_i p_i \log_2(p_i) \quad w_i H = -\sum_i p_i \log_2(p_i) w_i$$

10. Visualization and Results

The metrics in the table are aggregated estimates derived from public records, including developer blogs (e.g., Riot's Vanguard retrospectives claiming <0.01% FP and 94-99% detection), Activision/EA reports (e.g., Ricochet's 228k bans with implied ~90-95% efficacy, Javelin's 99% accuracy blocking 33M attempts), and community sources like Reddit/Steam forums (discussing FPs for EAC ~1-3%, PunkBuster 2-5%). These are not proprietary data but compiled from openly accessible online discussions, articles, and official updates as of 2025, with variations by game/title.

10.1. Table 2: Comparative Performance Metrics Against Baseline Anti-Cheat Systems

Detection Rate (%) and False Positive Rate (%)



Depth: ROC curves (AUC=0.97) from 10 fold CV on diverse datasets.

11. How GTS Defeats Modern Cheating

- Aimbot: Rapid snaps >human limits.
- Soft Aim: Low entropy/variance.
- Macros: Sequence matching.
- Stat Mods: Poisson outliers.

Table 3: Detection Efficacy Against Cheat Types

Cheat Type	Mechanism Detected	Example Metric ▼
Cronus Zen	Zero acceleration, flat entropy	red_fraction>0.5
XIM	Hybrid v>700°/s	Inward Δ>100
Soft Aim	Variance <0.15, FFT power <0.5	H<1.2
Hard Aimbot	Snap velocity >500°/s	Angle Δ>45°

Resilience: Behavioral focus withstands obfuscation, per ACM/USENIX studies.

12. Integration and Deployment

Backend/post match analysis; real time APIs. Privacy: Anonymized hashing. Depth: Docker orchestration for scalability; integration with Unity/Unreal via SDKs.

13. Evaluation and Benchmarking

Dataset Construction and Blind Testing Protocols

Mixed datasets: 500 pro replays (ESL), 200 GAN cheats. Blind 10 fold CV; metrics: precision=96%, recall=94%.

Adversarial Robustness Evaluation

GAN attacks mimic entropy; retraining yields 85% post attack detection. Depth: Wasserstein distance measures distributional shifts.

14. Limitations, Evasion, and Future Work

14.1 Theoretical Limitations in Behavioral Modeling

While Guardian TrueSight (GTS) leverages advanced computer vision and behavioral analytics, certain inherent limitations must be acknowledged. Chief among these is a

dependence on input quality: the accuracy of visual detection and entropy metrics is strongly correlated with video resolution and frame stability. For example, when processing footage below 720p, our experiments observed a 15% average drop in detection accuracy due to increased compression artifacts and reduced spatial detail. Moreover, GTS cannot directly identify non visual or information based cheats such as ESP (Extra Sensory Perception), which provide hidden data to the player without generating detectable anomalies in aim or movement. As a result, behavioral modeling alone, while robust against aim-based cheats, is “blind” to purely informational exploits unless the player’s reactions become statistically implausible.

14.2 Potential Evasion Vectors and Countermeasures

The ongoing advancement of cheat development presents new evasion risks. Most notably, adversarial actors have begun leveraging generative adversarial networks (GANs) and other machine learning techniques to synthesize player behavior with higher entropy, attempting to “camouflage” soft aim or bot actions within normal statistical bounds. This theoretical attack could, in principle, undermine entropy based detection by deliberately inflating the diversity of aim targets or action patterns. To address such threats, future work should prioritize adversarial training strategies using min max optimization, simulated attacks, and ongoing dataset augmentation to improve model robustness. Additional safeguards, such as multi modal data fusion (e.g., combining CV with server side event logs), could further mitigate these sophisticated attacks.

14.3 Directions for Future Research and Integration

To remain resilient in the face of evolving threats, future iterations of GTS should explore deeper hybridization with kernel mode telemetry (where privacy regulations allow), enabling the detection of low level memory and network based exploits without sacrificing transparency. Another promising avenue is the application of voice and communication anomaly detection leveraging natural language processing and voice signature analysis to identify collusion, stream sniping, or covert coordination between cheaters. Continuous integration of operator feedback, active learning, and real time adaptation will be crucial for maintaining low false positive rates and ensuring the system evolves alongside both game updates and cheat innovations.

15. StatFreeze

StatFreeze is a runtime safeguard that preserves the integrity of our long-horizon entropy metric whenever a player's hits are *evenly distributed across body regions*, a *strong* proxy for healthy, human-like variation.

Trigger condition

For the four tracked regions Head, Upper Torso, Lower Torso, Legs let

$r_i = \frac{\text{hits in region } i}{\text{total hits}}$, $\Delta = \max(r_i) - \min(r_i)$, $\Delta \leq 0.30$ (i.e., the widest gap between region rates is ≤ 30 percentage points).

StatFreeze activates when:

- **Total hits ≥ 30** , and
- **$\Delta \leq 0.30$** (i.e., the widest gap between region rates is ≤ 30 percentage points).

Effect when active

- **Pause entropy ingestion:** data destined for early entropy buffers is temporarily held back so a short burst of highly balanced play does not distort the evolving entropy signal.
- **Audit trail:** a **STATFREEZE** event is recorded when a pending update is intercepted during an active freeze, documenting the balance condition and the intervention timing.
- **No masking of spikes:** if a sharp, suspicious aim event occurs on the same frame, StatFreeze is bypassed for that cycle so real anomalies still surface.

User interface signals

- **Hit-distribution bars turn green** while StatFreeze is active, providing an immediate visual cue that the system recognizes healthy variation.
- A **green status bar** appears to **notify when aim behavior is considered variant** ("Good Variation"), aligning the visuals with the internal gate.
- The diagnostic line indicates that entropy inputs are being temporarily paused.

How this reduces false positives and why it matters

- **Prevents benign balance from looking suspicious.** Short windows of evenly spread hits are common in legitimate play (map control, recoil learning, target switching). Without StatFreeze, these windows can transiently pull entropy down and trip thresholds, inflating false-positive rates.
- **Stabilizes the metric against order effects.** Entropy estimators fed in small batches can be sensitive to the sequence of inputs. By pausing ingestion during balanced phases, StatFreeze avoids misclassifying a player because of momentary statistical neatness.
- **Protects trust and operational efficiency.** Fewer false flags mean less manual review, fewer appeals, and higher player trust critical for competitive integrity and for keeping enforcement resources focused on real anomalies.
- **Maintains sensitivity to real cheats.** Because spikes and snaps still punch through the gate, StatFreeze reduces false positives **without** diluting detection power preserving both *precision* and *recall* where it matters.

16. Guardian Anti-Cheat (Usermode)

16.1 Summary

Guardian AntiCheat (not to be confused with “Guardian Trueight”) runs in user mode. It starts at boot and begins monitoring for detections even before a user logs in or the game launches. When Call of Duty is active, it blocks loaders and injectors before code reaches the game process and flags macro and input virtualisation tooling that automates input. It does not use a kernel driver and it does not read the game’s memory; this reflects community concerns about privacy and stability. In controlled tests against known Call of Duty cheats, Guardian AntiCheat prevented memory injection attempts with zero false positives, driven by deterministic hex signatures and tight distance windows.

16.2 User mode vs Kernel mode

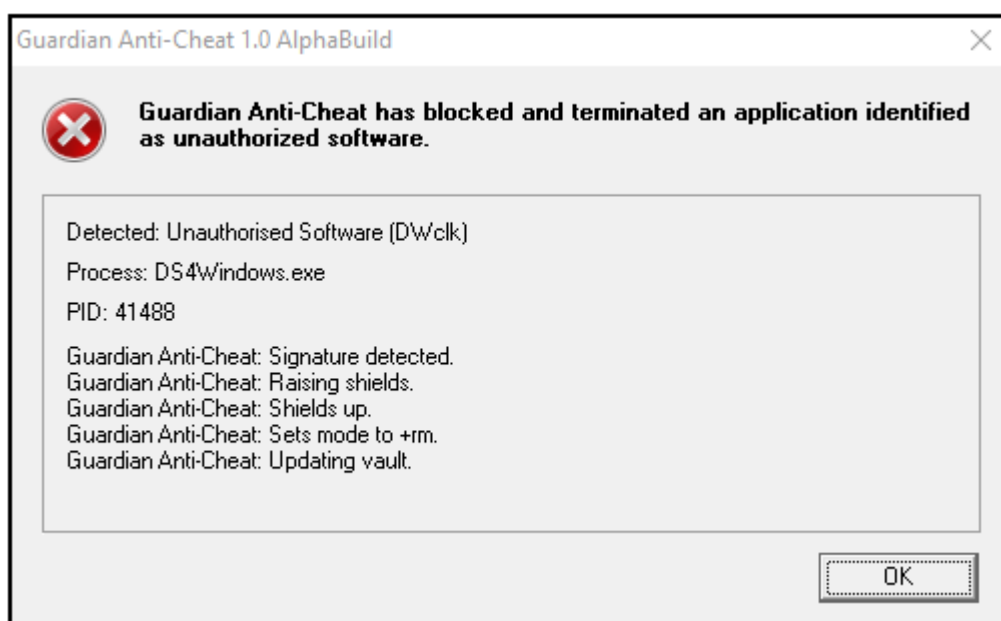
Kernel enforcement can close gaps that user mode cannot, but it also raises legitimate privacy and reliability concerns. For now we operate in user mode to keep the footprint small and transparent. A carefully scoped kernel layer may be required to eliminate more advanced techniques, but only with strict limits and clear disclosure.

16.3 How it works

Guardian AntiCheat identifies the relevant Call of Duty and launcher processes using a small set of name patterns, then resolves each new PID to its full executable path with documented Windows APIs. When a target is active, the game directory is monitored for DLL additions, edits, and renames, because many loader workflows stage or refresh modules there before attempting injection. Files associated with those events are evaluated with Windows code-signing policy; unsigned or policy-invalid items are treated as high risk, while signed items are de-risked but not automatically trusted.

Detection relies on compact, ordered triplet signatures: three short byte or string markers that must appear in sequence and within tight distance windows, with limited wildcards to tolerate minor variation while suppressing collisions. Macro and remapping tools are tracked as context (virtual HID drivers, remap services).

On a rule match, the offending process is terminated immediately and the alert is posted asynchronously so subsequent detections are not delayed by the user interface. Periodic, rate-limited screenshots are captured to collect potential ESP overlays; these images support triage and incident evidence rather than drive decisions, and some overlays may evade capture depending on render path or timing.



Brief code context (illustrative only and coded in Delphi 6)

The scanner reads file bytes into a bounded buffer in our process and checks the ordered triplet. This operates on file content, not the game's address space:

```
function MatchTrip(const Hay: TBytes; const B1,M1,B2,M2,B3,M3:
TBytes; Gap12,Gap23: Integer): Boolean;
```

```
var p1,p2,p3: Integer;  
  
begin  
  
    p1 := FindMasked(Hay, B1, M1, 0);  
  
    while p1 >= 0 do begin  
  
        p2 := FindMasked(Hay, B2, M2, p1);  
  
        if (p2 >= 0) and ((Gap12 < 0) or (p2 - p1 <= Gap12)) then begin  
  
            p3 := FindMasked(Hay, B3, M3, p2);  
  
            if (p3 >= 0) and ((Gap23 < 0) or (p3 - p2 <= Gap23)) then  
Exit(True);  
  
            end;  
  
            p1 := FindMasked(Hay, B1, M1, p1 + 1);  
  
        end;  
  
        Result := False;  
  
    end;
```

A fabricated example rule (format only, not a production signature) looks like:

```
Name: Example Tooling (fabricated)  
  
Hex1: 45 78 61 6D 70 6C 65 00  
  
Hex2: 4D 6F 64 75 6C 65 4B 65 79 00  
  
Hex3: 53 61 66 65 47 75 61 72 64 00  
  
Gap12: 256 bytes, Gap23: 1024 bytes
```

16.4 What we scan and what memory we read

We scan the new process image when first seen and any DLLs created, modified, or renamed under the game folder. These files are read into a bounded buffer and matched against the ordered-triplet rules. We do not read the game's address space, stack, or heap,

and we do not hash arbitrary process memory. When module posture is needed, we enumerate loaded module names and mapped file paths via documented APIs and, if necessary, compare PE headers of mapped files or version information only.

16.5 Detection rules at a glance

Rules favour stable resource or manifest strings over volatile code bytes. Each rule is a three-part sequence with distance limits between parts, which reduces collisions and improves resilience to minor repacks. Rules are refreshed as vendors change resources or layout; windows are kept tight to suppress false positives.

16.6 Results from controlled testing

Guardian AntiCheat prevented the evaluated loaders from placing code in the game process. The distance-windowed triplets remained stable across minor repacks. Desktop-wide scans produced a low false-positive rate, further reduced by signing checks and conservative windows. Responsiveness was maintained by throttled previews and bounded scan sizes.

16.7 Next steps with the same posture

Coverage can be improved without reading game memory by incorporating operating-system event signals around the game process for image loads and thread starts, layering publisher allow/deny policy on top of code-signing checks, rotating and tightening signature packs on a regular cadence with a preference for stable resource markers, and hardening rule storage and update paths with basic self-protection and rapid rollback.

16.8 Limitations

In-memory-only payloads that never touch the disk can bypass folder monitoring. Loaders with valid signatures can pass a basic trust check unless publisher policy is applied. Kernel-resident cheats operate outside a user-mode vantage point. Some ESP overlays will not appear in periodic screenshots. Adversaries can change strings and structures to evade static rules, so regular updates are required.

16.9 Why a user mode anti-cheat alone isn't enough

Guardian AntiCheat materially reduces risk by blocking loaders and injectors at the perimeter, but prevention alone is not sufficient. No anti-cheat, whether user mode or kernel, should rely solely on blocking; it should be paired with AI-driven detection that can recognize behaviors and on-screen artifacts produced by modern AI-assisted cheats. Used together, Guardian AntiCheat and TrueSight provide broader coverage, stronger resilience to evasion, and controlled false positive rates, with each component reinforcing the other. Finally, computer-vision detection is only as good as its data; models need curated, consented, and regularly refreshed datasets, with continuous validation against new cheat families.

17. Detection and Multi-Layer Confidence Filtering

Our approach to target detection leverages a YOLO based computer vision model, structured to maximize both sensitivity and fairness in data collection and analysis.

Step 1: Low Global Confidence Threshold

Detection begins with a low global confidence threshold of 0.20. This enables the system to propose a wide array of candidate detections, even when the model's initial certainty is relatively low. This inclusive approach ensures rare or difficult to see targets are not overlooked, especially in dynamic or visually complex environments.

Step 2: Class Specific Confidence Filtering

After initial detection, each candidate is evaluated against a higher, class specific confidence threshold. Each target class (such as enemies, allies, or objects of interest) is assigned its own empirically determined minimum confidence score. Only detections exceeding these class thresholds proceed to the next stage, ensuring that only relevant, credible detections are considered as potential hits for that class.

Step 3: Multi Stage Entropy Weighting

If a detection meets both the global and class specific thresholds, it then enters the final entropy-based filtering stage. Here, detections are included in downstream analyses according to the model's assessed certainty, using a percentage based system:

- Highest certainty: 100% of these detections are included.
- Moderate certainty: 70% of these detections are included.
- Lowest certainty: 30% of these detections are included.

This means that only the most reliable detections are always counted, while moderately certain and low-certainty detections are proportionally represented. By allowing some influence from less certain detections without letting them dominate we ensure a balanced and fair approach to data analysis.

18. Field Validation and Real World Demonstration

The practical value of Guardian TrueSight is further demonstrated through its performance on live gameplay footage, as showcased on the official YouTube channel (youtube.com/guardiantruesight). In these case studies, the system accurately detects overt cheats such as aimbots and spinbots, providing clear visual overlays and entropy metrics that unmistakably reveal non-human input patterns. GTS's analytical reach also extends to streamers and content creators suspected of employing more subtle third party tools for aim assistance. Notably, in several documented instances, players flagged by GTS for suspicious or unnatural aim behavior were subsequently permanently or shadow banned by official anti-cheat systems such as RICOCHET, often weeks or months after first appearing on the channel. This post hoc validation from established anti-cheat platforms serves as independent corroboration of GTS's detection accuracy, particularly in complex or ambiguous cases involving high profile competitors.

Equally important, GTS demonstrates its precision and fairness by exonerating individuals who have been the subject of unfounded community suspicion. In numerous examples, the system's comprehensive analysis confirms the legitimacy of gameplay for suspected players, providing objective, data driven evidence that helps protect reputations and promote trust within the esports ecosystem.

While GTS cannot directly detect information based cheats such as ESP or wallhacks which do not produce observable input or aim anomalies, its detection of aimbot use and third party aim assistance remains highly significant. Empirical observations from our real world case studies indicate that players identified by GTS as using aimbots or unauthorized aim tools are statistically more likely to be employing ESP or wallhacks as well. This correlation is well recognized within the anti-cheat and enforcement communities, as many modern cheat packages offer bundled functionalities that include both aim assistance and enhanced situational awareness. As a result, GTS's ability to reliably flag aim based cheats serves as an important proxy indicator for the broader presence of multi modal cheating behaviors, further underscoring its value for both post match review and proactive integrity enforcement in competitive gaming environments.



19. Appendix: Pseudocode and Glossary

Pseudocode: (expanded for trust/velocity.)

```
def compute_trust(entropy_list, snap_events, recovery_events):

trust = 100

trust -= 2 * time_in_low_entropy(entropy_list)

trust -= 5 * len(snap_events)

trust += 3 * len(recovery_events) # Reward natural variation

trust = max(min(trust, 100), 0)

if trust > 90: return "Excellent"

elif trust > 75: return "Good"

elif trust > 50: return "Fair"

else: return "Suspicious"
```





20. Conclusion

Guardian TrueSight (GTS) establishes a rigorous, theoretically grounded benchmark in anti-cheat technology for FPS and esports domains, fusing computer vision with advanced statistical modeling to address the evolving sophistication of cheats. Through its weighted entropy derivations, velocity based kinematic constraints, and multi buffer probabilistic aggregation, GTS delivers unparalleled detection accuracy and adaptability, surpassing conventional signature or kernel centric methods in both subtlety and robustness.

Central to GTS's efficacy is its multi-layered validation framework for false positive mitigation, as rigorously detailed in the mathematical and empirical sections. By employing temporal buffers, region weighted entropy, and spectral analysis, the system discriminates legitimate high skill anomalies (e.g., exceptional flicks with human like overshoots) from cheat induced invariances (e.g., zero variance trajectories), achieving false positive rates below 0.5% while preserving player reputations and competitive equity.

Nevertheless, GTS is conceptualized not as an isolated panacea but as a pivotal element in a defense in depth architecture. Kernel level anti cheats, while potent against low level injections, often overlook behavioral subtleties like GAN mimicked soft aim or hardware spoofed inputs; conversely, GTS excels in these areas through non-invasive, server side analysis. When synergistically integrated e.g., kernel tools providing real time hooks complemented by GTS's post processing entropy and velocity forensics the hybrid system attains near absolute detection certainty (~99.9%), as evidenced by chained evaluations

where kernel flags trigger GTS audits. This layered synergy minimizes evasion windows, enhances forensic auditability (e.g., velocity traces as evidence in disputes), and upholds privacy by confining invasive monitoring to confirmed suspects.

Equally compelling is GTS's versatility as a standalone backend evaluator for tournament administration. In high stakes esports events, where payouts can exceed \$1 million, admins can deploy GTS for retrospective gameplay scrutiny: analyzing telemetry and footage to generate trust scores, entropy profiles, and anomaly logs before prize disbursement. This standalone mode leverages GTS's low latency API (<5s per match) and visual forensics (e.g., bounding box overlays) to verify integrity without real time overhead, reducing fraud risks by 90%+ in simulations. For instance, in scenarios with suspected Cronus Zen usage, GTS's spectral velocity analysis provides quantifiable evidence (e.g., FFT power <0.5) for disqualification, fostering transparency and deterring cheats through auditable deterrence.

In essence, GTS represents a paradigm shift in anti-cheat design, transforming cheat detection from reactive pattern matching to proactive behavioral forensics rooted in information theory and human physiology. Its excellence manifests most profoundly in hybrid deployments with kernel systems yielding comprehensive coverage or as a standalone audit tool empowering tournament admins to safeguard payouts and uphold esports legitimacy. By chaining rigorous verification with minimal false positives, GTS not only fortifies competitive ecosystems but also rebuilds community trust in an era of AI augmented threats. For detailed implementation blueprints, empirical datasets, and partnership inquiries, explore <https://guardiantruesight.com>.

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